

1

2 WHAT IS CLAIMED IS:

3 1. A process controller comprising:

4 controller variable inputs comprised of measurements of  
5 process variable inputs of the process being controlled;  
6 a dynamic predictive model, of the process being  
7 controlled, with dynamic predictive model parameter(s), for  
8 receiving current variable input values wherein the dynamic  
9 predictive model parameter(s) change(s) dependent on said  
10 variable input values received by the controller; and  
11 output(s) from the dynamic model for generating controller  
12 outputs for effectuating change to the process being  
13 controlled.

14 2. The controller of claim 1 wherein the dynamic predictive  
15 model is further comprised of:

16 a physical model with physical model parameters; and  
17 an empirical model which adjusts the physical models  
18 parameters based on the controller variable inputs.

19 3. The controller of claim 2 wherein the empirical models  
20 adjustments to the physical models parameters based on the  
21 controller variable inputs is further based on historical  
22 controller inputs.

- 1 4. The controller of claim 2 where the physical model is a  
2 first principles model of the process being controlled.
- 3 5. The controller of claim 2 where the empirical models is  
4 non-linear model.
- 5 6. The controller of claim 2 where the non-linear model is a  
6 neural network.
- 7 7. The controller of claim 2 wherein the physical model is a  
8 first principles model of the process being controlled and  
9 the empirical model is a non-linear neural network that  
10 adjusts the parameters of the first principle model based  
11 on the controller variable inputs.
- 12 8. The controller of claim 7 wherein the physical model is a  
13 first principles model of the process being controlled and  
14 the empirical model is a non-linear neural network that  
15 adjusts the parameters of the first principle model based  
16 on the current controller variable inputs.
- 17 9. The controller of claim 7 wherein the physical model is a  
18 first principles model of the process being controlled and  
19 the empirical model is a non-linear neural network that  
20 adjusts the parameters of the first principle model based  
21 on the current and historical controller variable inputs.
- 22 10. A process control system comprising:  
23 a distributed control system that further comprises:

1 a computing device operable to execute a first software  
2 tool that identifies variable inputs including at least one  
3 manipulated variable input and controlled variables  
4 associated with the process, wherein said first software  
5 tool is further operable to determine relationships between  
6 said variable input(s) and said controlled variables; and  
7 at least one controller operable to monitor said variable  
8 input parameter(s) and tune said manipulated variables.

9 11. The process control system of claim 10, wherein said  
10 relationships between said variable input(s) and said  
11 controlled variables comprises a first principle model(s)  
12 with model parameters wherein said first principle model  
13 parameter values are dependent on said variable input(s).

14 12. The process control system of claim 10, further comprising  
15 neural networks utilized to identify said model parameters.

16 13. The process control system of Claim 10, wherein said step  
17 of determining relationships between said variable input(s)  
18 and said controlled variables utilizes a neural network.

19 14. The process control system of claim 10, wherein said step  
20 of determining the relationship between said variable  
21 inputs and said controlled variables utilizes a combination  
22 of physical models and empirical methods.

- 1 15. The process control system of claim 13 wherein said  
2 physical models and empirical methods are combined in  
3 parallel and/or in series.
- 4 16. The process control system of claim 13 wherein said  
5 physical model parameter(s) varies over an operating range.
- 6 17. The process control system of claim 14 wherein said  
7 physical model is a function of said variable input(s).
- 8 18. The process control system of claim 16 wherein said  
9 physical model comprises first principle parameters which  
10 vary with said variable input(s), wherein empirical methods  
11 comprise a neural network used to identify first principle  
12 parameter values associated with said variable input(s) and  
13 wherein said neural network updates said first principle  
14 parameters with values associated with said variable  
15 input(s).
- 16 19. The process control system of claim 18 wherein said neural  
17 network is trained.
- 18 20. The process control system of claim 18 wherein said neural  
19 network is trained according to at least one method  
20 selected from the group consisting of: gradient methods,  
21 back propagation, gradient-based nonlinear programming

1 methods, sequential quadratic programming, generalized  
2 reduced gradient methods, and non-gradient methods.

3 21. The process control system of claim 20 wherein gradient  
4 methods require gradients of an error with respect to a  
5 weight and bias obtained by numerical derivatives.

6 22. The process control system of claim 20 wherein gradient  
7 methods require gradients of an error with respect to a  
8 weight and bias obtained by analytical derivatives.

9 23. The process control system of claim 10 wherein said control  
10 variable comprises a magnetic field strength, shape,  
11 location and/or orientation and said controlled variable  
12 comprises particle positions within a particle accelerator.

13 24. The process control system of claim 23 wherein a step of  
14 tuning the control variable comprises adjusting a connector  
15 magnet and/or quadrapole magnet.

16 25. A dynamic process controller predicting a change in the  
17 dynamic variable input values to the process to effect a  
18 change in the controlled variable output of the process  
19 from a current controlled variable output value at a first  
20 time to a different and desired controlled variable output  
21 value at a second time, comprising:

1 a dynamic predictive model for receiving the current  
2 variable input value, wherein said dynamic predictive model  
3 changes dependent upon said variable input value, and the  
4 desired controlled variable output value, and wherein said  
5 dynamic predictive model produces a plurality of desired  
6 controlled variable input values at different time  
7 positions between the first time and the second time to  
8 define a dynamic operation path of the process between the  
9 current controlled variable output value and the desired  
10 controlled variable output value at the second time; and  
11 an optimizer for optimizing the operation of the dynamic  
12 controller over a plurality of the different time positions  
13 in accordance with a predetermined optimization method that  
14 optimizes the objectives of the dynamic controller to  
15 achieve a desired path, such that the objectives of the  
16 dynamic predictive model vary as a function of time.

17 26. The dynamic process controller of claim 25, wherein said  
18 dynamic predictive model comprises:

19 a dynamic forward model operable to receive variable input  
20 values at each of said time positions and map said variable  
21 input values to components of said dynamic predictive model  
22 associated with said received variable input values in  
23 order to provide a predicted dynamic controlled variable  
24 output value;

1 an error generator for comparing the predicted dynamic  
2 controlled variable output value to the desired controlled  
3 variable output value and generating a primary error value  
4 as the difference for each of said time positions;  
5 an error minimization device for determining a change in  
6 the variable input value to minimize the primary error  
7 value output by said error generator;  
8 a summation device for summing said determined variable  
9 input change value with an original variable input value,  
10 which original variable input value comprises the variable  
11 input value before the determined change therein, for a  
12 plurality of time position to provide a future variable  
13 input value as a summed input value; and  
14 a controller for controlling the operation of said error  
15 minimization device to operate under control of said  
16 optimizer to minimize said primary error value in  
17 accordance with said optimization method.

18 27. A method for controlling operating process, comprising the  
19 steps of:  
20 identifying variable input(s) and controlled variables  
21 associated with the process, wherein at least one variable  
22 input is a manipulated variable;

1       determining relationships between said variable input(s)  
2       and said controlled variables wherein said relationship  
3       comprises models, and wherein parameters within said model  
4       are dependent on said variable inputs; and  
5       tuning said manipulated variable to achieve a desired  
6       controlled variable value.

7   28. The method of Claim 27, further including the step of  
8       determining the relationship between the variable inputs  
9       and the model parameters wherein said relationship  
10      comprises a model.

11   29. The method of Claim 27, wherein said step of identifying  
12      relationships between variable inputs and control variables  
13      utilizes neural networks.

14   30. The method of Claim 28, wherein said step of identifying  
15      relationship between the variable input(s) and dynamic  
16      model parameters utilizes neural networks.

17   31. The method of Claim 27, wherein said step of determining  
18      relationships between said variable input(s) and said  
19      controlled variable(s) utilizes a combination of physical  
20      models and empirical methods.

21   32. The method of Claim 31, wherein said physical models and  
22      empirical methods are combined in series.



1 33. The method of Claim 31, wherein said physical models and  
2 empirical methods are combined in parallel.

3 34. The method of Claim 31, wherein said physical model varies  
4 over an operating range.

5 35. The method of Claim 34, wherein said physical model is a  
6 function of said input parameters.

7 36. The method of Claim 35, wherein said physical model  
8 comprises first principle parameters which vary with said  
9 variable inputs, wherein empirical methods comprise a  
10 neural network used to identify first principle parameters  
11 values associated with said variable input(s), and wherein  
12 said neural network updates said first principle parameters  
13 with values associated with said variable input(s).

14 37. The method of Claim 36, wherein said neural network is  
15 trained.

16 38. The method of Claim 37, wherein said neural network is  
17 trained according to at least one method selected from the  
18 group consisting of gradient methods, back propagation,  
19 gradient-based nonlinear programming (NLP) methods,  
20 sequential quadratic programming, generalized reduced  
21 gradient methods, and non-gradient methods.

1 39. The method of Claim 38, wherein gradient methods require  
2 gradients of an error with respect to a weight and bias  
3 obtained by either numerical derivatives or analytical  
4 derivatives.